AIRLINE PRICING BEHAVIOUR UNDER LIMITED INTERMODAL COMPETITION[*]

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Abstract

This paper empirically analyses airline pricing for short-haul flights in contexts with no credible threat of intermodal competition. To this end, we explore the southern Italian market since it is less accessible by other transport modes and fares are, thus, the straight outcome of air-related competition. We show that market power matters, in fact, depending on the level of intramodal competition, airlines apply differentiated mark-ups. Besides, consistently with the implementation of intertemporal price discrimination (IPD), we find a non-monotonic intertemporal profile of fares with a turning point at the 44^{th} day before departure. Finally, we provide evidence that airlines are more likely to engage in IPD in more competitive markets.

Key words: airfares, market structure, intertemporal price discrimination

JEL: L11, L13, L93

[*]Special thanks to Marco Alderighi, Richard Arnott, Michele Bernasconi, Volodymyr Bilotkach, André de Palma, Alberto Gaggero, Andrew Goetz, Kai Hüschelrath, Marc Ivaldi, Claudio Piga and Wesley W. Wilson for useful insights on earlier versions. The authors would also like to thank participants at 17th ATRS Conference, 5th ICEEE, 5th CRNI Conference, 39th EARIE Conference, 14th SIET Conference, RCEA Workshop on "The economics and management of leisure, travel and tourism" and 32th AISRe Conference for very helpful comments and suggestions. All remaining errors are ours.

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I INTRODUCTION

There are three sources of competition in the airline market for short-haul flights which jointly affect fares. Airlines compete with other airlines for the same city-pair markets (intramodal competition). Moreover, airlines compete with other modes of transport (intermodal competition) as trains, especially high speed trains, and cars, which give the advantage to travel at any time. Finally, airlines compete with themselves by setting different fares in different time periods prior to departure. This pricing strategy is known as intertemporal price discrimination (IPD).

Past empirical contributions exploring pricing behaviour and competition in air transportation were not able to control for the effect of intermodal competition which, we can expect, affected the results. This paper differs from existing works as it attempts to study airline pricing for short-haul flights in contexts with no credible threat of intermodal competition in order to shed light on pricing behaviour in response to the pure air-related competition. To this scope, we analyse a market, southern Italy, which definitely shows a highly limited degree of intermodal competition. On the connections considered, in fact, services by alternative modes, including road transport, require, on average, more than seven times the same travelling time as airline connections. For these peripherical areas, air transport is, thus, often the only realistic alternative. It can be assumed, therefore, that airline pricing strategies are the straight result of air-related competition. The pricing behaviour of airline companies show also high variability of fares per mile which unlikely can be justified by cost differentials, while might be considered as evidence of different degrees of market power and, thus, the capacity to determine mark-ups.

In this paper, we deal, basically, with two issues. The first is to measure the extent to which intramodal competition determines fares. The second is to shed light on the intertemporal profile of fares to verify if airlines engage in IPD and whether IPD is of monopolistic-type or competitive-type. As for the former type, market power is required to price discriminate as it enhances the ability of firms to set and maintain higher mark-ups (Tirole, 1988). As for the latter type, market power is not required to sustain price discrimination if consumers show heterogeneity of brand preferences (Borenstein, 1985 and Holmes, 1989) or demand uncertainty about departure time (Dana, 1998).

The dataset we use to address the research question is unique. It covers routes that originates in southern Italy and are operated from November 2006 to February 2011. Data on fares were collected from airline website to replicate consumer behaviour when making reservations. Unlike previous contributions, we simulate the purchase of round-trip fares instead of one-way fares. In this way, we effectively replicate the demand side since travellers use to purchase round-trip tickets rather than one-way tickets. In addition, we precisely recreate the supply side as we can clearly see if, for each round-trip flight, a carrier is a feasible alternative for travellers and an effective competitor.

Our results on short-haul markets with no alternative modes of transport point out that when the intramodal competition reduces, airlines set higher fares since they exploit the greater market power arising from a concentrated market structure. Specifically, 10% increase of market share allows carriers to post up to 6.4% higher fares. Consistently with the implementation of IPD, we find a non-monotonic intertemporal profile of fares - which can be roughly approximated by a J-curve - with a turning point at the 44^{th} day before departure. Our claim is that, on the one hand, the non-monotonicity would be the evidence that airlines exploit consumer bounded rationality. Actually, a common wisdom among travellers is "the later you buy, the more you pay the ticket", thus price sensitive consumers tend to buy in advance. Airlines, aware of this, can extract a greater surplus by setting moderately higher fares for very-early purchasers that will buy the tickets believing to pay the cheapest fares. On the other hand, a higher fare for very-early purchasers can be seen as a fee for risk-aversion. Finally, we provide evidence of a competitive-type IPD as airlines seem to be more likely to engage in IPD in more competitive markets.

The remainder of the paper unfolds as follows. In Section 2 we survey the relevant literature. In Section 3 we present the empirical strategy and in Section 4 we give a description of the data. In Section 5 we discuss the results and in Section 6 we draw conclusions. The robustness check is provided in the appendix.

II LITERATURE REVIEW

The literature on which the current work is based concerns pricing in air transportation and the factors influencing it. We initially review papers which analyse the effect of airline market structure on fares, then we focus on works looking at price discrimination and, in particular, at intertemporal price discrimination (IPD). We conclude the survey with contributions exploring the relationship between market structure and price discrimination.

The first to study the impact of market structure on fares was Borenstein (1989) on the US airline industry. He develops a model using market share at both route and airport level. Results indicate that market share, whatever measure adopted, influences carrier's ability to raise fares since the dominant presence of an airline at an airport increases its market share on the routes included in that airport. However, Evans and Kessides (1993) point out that, when controlling for inter-route heterogeneity, market share on the route is no longer relevant in determining fares, which are, instead, determined by carriers' market share at the airports. More recently, some contributions explored the European airline markets. Unlike the US market, Carlsson (2004) finds that market power, measured by the Herfindahl index, does not have a significant effect on fares whereas it influences flight frequencies. Consistently, Giaume and Guillou (2004) find a negative and, often, non significant impact of market concentration for connections from Nice Airport (France) to European destinations. Bachis and Piga (2007a) measure the effect of market concentration at the origin airport on fares applied by British carriers, considering either the route or the city-pair level. Their results reveal the existence of a large degree of substitutability between the routes within a city-pair. A greater market share at route level leads to higher fares while at city pair level it does not. Gaggero and Piga (2010) find that higher market share and Herfindhal Index at the city-pair level leads to higher fares on routes connecting the Republic of Ireland to the UK. Finally, Brueckner et al. (2013) provide a comprehensive analysis of competition and fares in domestic US markets, focussing on the roles of LCCs and FSCs. They find that FSC competition in an airport-pair market has a limited effect on fares, whilst competition in a city-pair market has no effect. In contrast, LCC competition has a strong impact on fares, whether it occurs in airport-pair markets or in city-pair markets.

As far as concerns price discrimination, the main difference between static and intertemporal price discrimination is that two different markets are coverd in the former case whereas the same market is periodically covered in the latter case. In a theoretical model with two time periods Logfren (1971) shows that a seller applies, for the same good, higher prices to consumers with higher purchasing power in the first period and lower prices to consumers with lower purchasing power in the second period. Stokey (1979) implicitly extend Logfren's framework to a continuous of periods. She claims that IPD occurs when goods are "introduced on the market at a relatively high price, at which time they are bought only by individuals who both value them very highly and are very impatient. Over time, as the price declines, consumers to whom the product is less valuable or who are less impatient make their purchases".[1] In her paper reference is made to commodity such books, movies, computers and related programmes. The concept, however, has had application to the airline industry where IPD consists of setting different fares for different travellers according to the days missing to departure when the ticket is bought. However, differently from markets for commodities, in the airline industry the intertemporal profile of fares is increasing. Using IPD, airlines exploit travellers' varied willingness to pay and demand uncertainty about departure time. Price-inelastic consumers, usually business travellers, use to purchase tickets close to departure date, whilst price-elastic consumers, usually leisure travellers, tend to buy tickets in advance.[2] Actually, Gale and Holmes (1992, 1993) prove that through advance-

[1] See page 355.

[2] Travellers' heterogeneity appears to be a necessary condition to successfully implement price discrimination strategies. In a theoretical contribution Alves and Barbot (2009) illustrates that low-high pricing is a dominant strategy for LCCs only if travellers, on a given route, show varied willingness to pay.

purchase discounts a monopoly airline can increase the output by smoothing demand of consumers with weak time preferences over flight times and extract the surplus of consumers with strong preferences. More recently, Möller and Watanabe (2010) investigate further on advance-purchase discounts versus clearence sales, showing that the former pricing strategy is preferred to the latter for airline tickets because their value is uncertain to buyers at the time of purchase and resaling is costly or difficult to implement.

The intertemporal profile of fares has been also empirically explored. McAfee and te Velde (2006) find out that one week before the departure there is a significant rise in fares, which is on the top of the rise of two weeks before the departure. Bachis and Piga (2007a) show that fares posted by British LCCs follow an increasing intertemporal profile. Instead, Bachis and Piga (2007b), who examine UK connections to and from Europe, and Alderighi and Piga (2010), that focussed on Ryanair pricing in the UK market, find a U-shaped fare intertemporal profile. Gaggero and Piga (2010) show that fares for Ireland-UK connections follows a J-curve. Gaggero (2010) argues that there are three categories of travellers: early-bookers and middle-bookers, usually leisure travellers, and late-bookers, mostly business travellers. Early-bookers have a slightly inelastic demand. Families planning holidays are, for instance, willing to pay moderately higher fares to travel during vacations. Middle-bookers exhibit the highest demand elasticity as they are more flexible and search for the cheapest fares. Late-bookers reveal an inelastic demand. A business traveller typically books the ticket a few days before departure, with fixed travel dates and destination. As a result, fare intertemporal profile is J-shaped as it reflects a pattern opposite to that of travellers' demand elasticity.[3]

One strand of literature explores the relationship between market structure and price discrimination to find out whether airlines are more willing to engage in price discrimination strategies when markets are more or less competitive. Traditionally market power en-

[3] Abrate et al (2010) show that in the hotel industry, hoteliers undertake IPD with two opposite trends. If a room is booked for the working days, last minute prices are lower. Instead if a room is reserved for the weekend, last minute prices are higher.

hances the ability of firms to price discriminate. A monopolist can set and maintain higher mark-ups.[4] In the oligopolistic airline industry, when competition increases, carriers lose this ability. Mark-ups associated with the fares paid by the less price-sensitive (business) travellers decrease and align with the ones of the more price-sensitive (leisure) travellers. However, Borenstein (1985) and Holmes (1989) show that market power is not required to sustain price discrimination if consumers show heterogeneity of brand preferences. Business travellers prefer the long-run savings given by loyalty programmes, whilst leisure travellers disregard carriers for short-run savings. Sorting consumers based on strength of brand preference is a successful strategy and competition does not prevent firms from pursuing it. When competition increases, the mark-ups applied to leisure travellers decrease, whereas the mark-ups applied to business travellers remain almost unchanged. As a result, price discrimination increases as competition increases. Further, Gale (1993) prove that competition to conquer less time-sensitive travellers is stronger in an oligopoly than in a monopoly. Competition reduces fares on the lower end of the distribution thus enhancing price dispersion. Finally, Dana (1998) shows that price discrimination, in the form of advance purchase discounts, does not require market power to be implemented. Consumers with more certain demands are willing to buy in advance because the presence of consumers with less certain demand could lead to an increase in prices.

Some empirical papers consider price dispersion as the result of price discrimination. Borenstein and Rose (1994) explore the US airline industry and provide evidence of competitive-type price discrimination: lower price dispersion arises in more concentrated markets. Consistently, Carbonneau et al. (2004) show that more competition is correlated with more price dispersion. Later, Gerardi and Shapiro (2009) revisit the analysis of Borenstein and Rose (1994). They find the same results when they replicate the cross-sectional model of Borenstein and Rose (1994). However, they have opposite results when performing a panel analysis.[5] Indeed, they provide evidence of monopolistic-type price discrimination: higher

[4] See Tirole (1988) chapter 3.

[5] Gerardi and Shapiro (2009) explain that the panel approach allows them to estimate the effect of compe-

price dispersion arises in more concentrated markets.

Stavins (2001), instead, measures price discrimination through ticket restrictions.[6] Consistently with Borenstein and Rose (1994), she provides evidence of competitive-type price discrimination in the US airline industry: ticket restrictions reduce fares although the effect is lower for more concentrated markets. Using the cross-sectional model of Stavins (2001), Giaume and Guillou (2004) get to the same results on intra-European connections.[7]

Gaggero and Piga (2011) provide a seminal contribution on the effect of market structure on intertemporal pricing dispersion focusing on the routes connecting Ireland and the UK. Consistently with Gerardi and Shapiro (2009), they find that few companies with a relatively large market share can easily price discriminate.

In contrast to the aforementioned contributions, Hayes and Ross (1998) find no empirical evidence of price discrimination and market structure in the US airline industry. Price dispersion is due to peak load pricing and it is influenced by the characteristics of the carriers operating on a given route. Consistently, Mantin and Koo (2009) highlight that price dispersion is not affected by the market structure. Instead, the presence of LCCs among the competitors enhances dispersion by inducing FSCs to adopt a more aggressive pricing behaviour.[8]

III EMPIRICAL STRATEGY

We define two models. The baseline model accounts for the effect of market structure and IPD on fares. The extended model allows for IPD to vary with market structure.[9]

tition by accounting for changes in the competitive structure of a given route over time rather than changes in competitive structures across routes.

[6] Ticket restrictions are the Saturday-night stay over requirement and the advance-purchase requirement.

[7] Besides the ticket restrictions used by Stavins (2001), Giaume and Guillou (2004) take into account some exogenous segmentations such as families, age groups, student status, and events.

[8] Alderighi et al (2004) find that when a LCC enters a given route, the FSC incumbent reacts by lowering both leisure and business fares. Further, Fageda et al. (2011) note that traditional carriers are progressively adopting the management practices of LCCs. In particular FSCs, through their low-cost subsidiaries, are able to price more aggressively and hence successfully compete with LCCs.

[9] The idea of measuring the net effect of price discrimination from varying the market structure has been inspired by the approach of Stavins (2001).

The baseline model:

$$\begin{aligned}\ln(P_{it}) &= \beta_0 + \beta_1 MarketStructure_i + \beta_2 BookingDay_t \\ &+\theta_3 FlightCharacteristics_i + \theta_4 ControlDummies_{it} \\ &+u_{it}\end{aligned} \tag{1}$$

The extended model:

$$\begin{aligned}\ln(P_{it}) &= \beta_0 + \beta_1 MarketStructure_i + \beta_2 BookingDay_t \\ &+\beta_3 (MarketStructure_i * BookingDay_t) \\ &+\theta_4 FlightCharacteristics_i + \theta_5 ControlDummies_{it} \\ &+u_{it}\end{aligned} \tag{2}$$

where i indexes the round-trip flight and t the time. Each flight i is defined by the route, the carrier and the date of departure and return. We have a daily time dimension that goes from 1 to 60.

The dependent variable is the log of the fares. The variable *Booking Day* captures the effect of IPD and ranges from 1 to 60. In order to account for the potential non-linearity of *Booking Day*, we also add *Booking Day* squared to the model.

We use two indices of market structure at city-pair level:[10]

- *Market Share*, the average share of the daily flights operated by an airline at the two endpoints of a city-pair;
- *Herfindahl-Hirschman Index* (HHI), based on *Market Share*;

Flight Characteristics includes the following variables:

[10] We do not compute market structure variables at route-level because, working with a peripheral area, almost all the carriers could operate as a monopolist on a given route. We need the city-pair level to capture the real competition between carriers.

- *Holiday* is a peak-period dummy equal to 1 for flights occurring during summer holidays, winter holidays, bank holidays and public holidays, 0 otherwise.

- *LCC* is a carrier dummy equal to 1 for flights provided by LCCs, 0 otherwise.

Control dummies are:

- *Route dummies* to capture route-specific effects, demand and cost (or price) differences;

- *Year dummies* to account for macroeconomic factors equally affecting all flights in each year;

- *Month dummies* to capture seasonal effects;

- *Departure Time* and *Return Time*, two sets of four categorical dummies capturing the effect of the takeoff time: Morning (6:00-10:00), Midday (10:00-14:00), Afternoon (14:00-18:00) and Evening (18:00-24:00);[11]

- *Stay dummies* to control for the length of stay (i.e. how many days elapse between departure and return).

Finally, u_{it} is the composite errore term, where $u_{it} = \alpha_i + \varepsilon_{it}$. Specifically, α_i is the unobserved heterogeneity and ε_{it} is the idiosyncratic error term. Standard errors are clustered at flight level since observations on flights are not likely to be independent over time.

We assume that the market structure is exogenous. Basically, we agree with Stavins (2001) claiming that elements such as "entry barriers prevent new carriers from entering city-pair routes (e.g., limited gate access, incumbent airlines' hub-and-spoke systems, and scale economies in network size)".[12] Moreover, in the European Union there are the "grandfather rights": an airline that held and used a slot last year is entitled to do so again in the same season the following year. In the short run, then, market structure can be assumed to be fixed. The validity of the exogeneity assumption is tested as explained in the appendix.

[11] Based on Gaggero and Piga (2011).

[12] Stavins follows the approach of Graham et al. (1983).

We want to estimate coefficients of time-invariant variables, therefore we use the Random Effects (RE) Generalised Least Square (GLS) estimator. The RE estimator to be consistent requires the assumption that the right-hand side variables are not correlated with the unobserved heterogeneity α_i. The Robust Hausman test using the method of Wooldridge (2002) is performed after each regression to test the validity of that assumption and, hence, the consistency of RE estimates.[13]

IV DATA COLLECTION

Data on fares were collected to replicate real travellers' behaviour when making reservations. First, we identified plausible round-trips, then we retrieve data directly from airlines' website by simulating reservations.[14] We observed fares daily starting, generally, sixty booking days before departure. However, for some round-trip flights we have less than sixty observed fares, thus the panel is unbalanced. We define a dataset comprising 19,605 observations on 427 round-trip flights from November 2006 to February 2011. Our sample includes 10 city-pairs (see Table 1) and 11 airline companies.

[13] See Wooldridge (2002), pp. 290-91.

[14] We avoid any potential distortion on pricing strategies caused by online travel agencies that could set discounted fares.

TABLE 1

List of city-pair markets

Origin	*Destination*
Bari	Milan
Bari	Rome
Brindisi	Milan
Brindisi	Rome
Catania	Milan
Catania	Rome
Naples	Milan
Naples	Rome
Palermo	Milan
Palermo	Rome

Both FSCs and LCCs are considered (see Table 2); thus we chose the basic services (no add-ons) to make carriers' supply effectively comparable.

TABLE 2

List of airline companies.

Full Service Carriers	*Low Cost Carriers*		
AirOne	Alpieagles	Meridiana	Volare Web
Alitalia	Blu Express	MyAir	WindJet
Lufthansa	EasyJet	Ryanair	

We simulate the purchase of round-trip tickets, which gives us several advantages. Firstly, we effectively replicate the consumer behaviour since travellers use to purchase round-trip tickets rather than one-way tickets.[15] In addition to that, we precisely recreate the market structure as we can clearly see if, for each round-trip flight, a given carrier is a feasible alternative for travellers and an effective competitor. The use of round-trip fares allows also to account for peak-periods and to verify if airlines adjust the pricing behaviour during

[15] See, for instance, the analysis on airline travel demand carried out by Belobaba (1987).

phases of greater travel demand. Further, one-way ticket pricing differs depending on carrier type. For FSCs a round-trip fare is lower than sum of the correspondent two one-way fares. This pricing policy is not adopted by LCCs. To avoid distortions, previous contributions using one-way fares limit the empirical analysis to LCCs or to a few carriers. Instead, we do not encounter this problem and we are able to carry out a market analysis and compare pricing behaviour of all carrier types. In Table 3 we provide descriptive statistics.

TABLE 3

Descriptive statistics

Variables	*Obs*	*Mean*	*St. Dev.*	*Min*	*Max*
Fares	19605	153.80	84.85	11.92	690.49
Market Share	19605	0.405	0.286	0.065	1
HHI	19605	0.497	0.203	0.225	1
Booking Day	19605	24.672	14.889	1	60
Holiday	19605	0.458	0.498	0	1
LCC	19605	0.455	0.498	0	1

Our data sample has a good deal of variation in term of both fares and market structure indices. In fact, we observe either monopolistic or more competitive markets.

Further, in Table 4 we report the average fares per mile posted by the incumbent airline providing services for the city-pair included in the empirical analysis.

TABLE 4

Average round-trip fares per mile posted by the incumbent airline

Connection	*Avg fare per mile*	*Connection*	*Avg fare per mile*
BRI-FCO-BRI	0.4260	PMO-LIN-PMO	0.1587
BRI-LIN-BRI	0.1832	PMO-MXP-PMO	0.1225
BRI-MXP-BRI	0.2387	CTA-FCO-CTA	0.2594
BDS-FCO-BDS	0.3086	CTA-MXP-CTA	0.1421
BDS-LIN-BDS	0.1588	NAP-FCO-NAP	0.8788
BDS-MXP-BDS	0.1332	NAP-LIN-NAP	0.1976
PMO-FCO-PMO	0.2548		

From each origin, connections to Rome appear to be comparatively more expensive than connection to Milan, even thought point-to-point distances to Rome are shorter than point-to-point distances to Milan. This could be only partially explained by the cost of fuel. For short-haul flights, approximately the 35% of fuel is used on the take-off, which makes the cost function decreasing with distance. However, differences in fares do not seem to reflect only differences in costs, but, instead, would suggest that the incumbent airline applies different mark-ups to different connections. This preliminary evidence motivates a discussion in depth on fares' determinats.

It is worth looking at Figure 1 showing that the relationship between average posted fares and days missing to departure seems to be non-monotonic.

FIGURE 1

The intertemporal profile of fares.

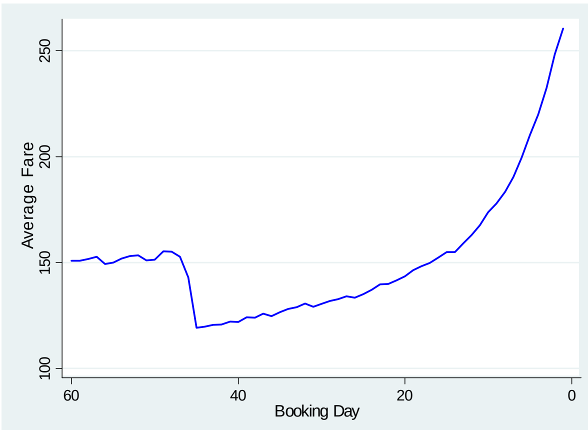
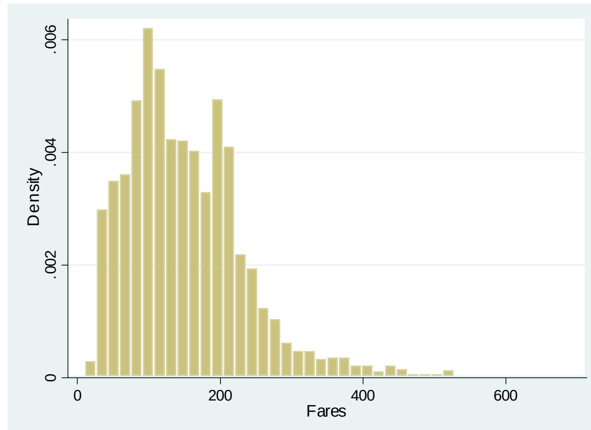


FIGURE 2

Density distribution of fares.



Airlines set the initial level of fares, subject to slight changes for, roughly, fifteen days, then fares are sharply decreased to the minimum level. Henceforth, airlines increase fares up to the departure day. The increment becomes steeper in the last fifteen days. We dwell into this when presenting regression results. Figure 2 shows the density distribution of fares. The mass of values is concentrated between 50 and 200 euros.

V RESULTS

In each regression tables we report the results of the Robust Hausman test which verify the assumption validity of uncorrelation between right-hand side variables and the unobserved heterogeneity. Results lead not to reject the null hypothesis that GLS estimator is consistent.

Estimation results reported in the tables contained in this section are organised as follows: columns (1) and (2) report regressions' output using the variable *Market Share*, while columns (3) and (4) report regressions' output using the variable *HHI.*

Table 5 shows the results of the Baseline Model. *Market Share* and *HHI* have a positive and highly significant impact on fares. Holding constant other variables, 10% increase in *Market Share* leads to 6.4% higher fares and 10% increase of *HHI* leads to 5.7% higher fares.

TABLE 5

Baseline Model

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0064***	0.0064***	0.0057***	0.0057***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Booking Day	-0.0141***	-0.0353***	-0.0141***	-0.0353***
	(0.0005)	(0.0013)	(0.0005)	(0.0013)
Booking Day^2		0.0004***		0.0004***
		(0.0000)		(0.0000)
Holidays	0.2082***	0.2112***	0.2310***	0.2341***
	(0.0521)	(0.0522)	(0.0554)	(0.0554)
LCC	-0.2249***	-0.2259***	-0.4047***	-0.4058***
	(0.0426)	(0.0426)	(0.0324)	(0.0325)
Hausman Test statistic	0.843	2.141	0.085	1.645
Hausman Test p-value	0.359	0.343	0.771	0.439
Observations	19,605	19,605	19,605	19,605

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported. *** p<0.01, ** p<0.05, * p<0.1.

Estimations are done, at first, with only the variable *Booking Day*. Its coefficient is negative and significant meaning that airlines do engage in IPD. Indeed, fares posted the day before appear to be 1.41% lower. We then include *Booking Day* squared to the regression equation to check for the non-linearity, as the graphical investigation suggests. The coefficient of *Booking Day* squared is positive and highly significant. *Booking Day* has a negative effect of fares until the turning point is reached at the 44^{th} day before departure. Beyond that day, it has a positive impact on fares. In the non-linear case, the marginal effect of *Booking Day* on fares is dependent on the level of *Booking Day*: $\frac{\partial \ln(P_{it})}{\partial Booking\ Day_t} = -0.0353 + 2 * (0.0004)\ Booking\ Day_t$.

We compute the marginal effect for given values of *Booking Day* which indicates how fares vary with respect to fares posted a day early.

TABLE 6

The marginal effect (β) of Booking Day (BD) on fares.

BD	β	*BD*	β	*BD*	β	*BD*	β
5	-0.0313	35	-0.0073	45	0.0007	51	0.0055
10	-0.0273	40	-0.0033	46	0.0015	52	0.0065
15	-0.0233	41	-0.0025	47	0.0023	53	0.0071
20	-0.0193	42	-0.0017	48	0.0031	54	0.0079
25	-0.0153	43	-0.0007	49	0.0039	55	0.0087
30	-0.0113	44	-0.0001	50	0.0047	60	0.0127

As shown in Table 6, from the 45^{th} day before departure, fares posted a day before are no longer cheaper. The non-monotonicity of fare intertemporal profile has received various interpretations in the literature.[16] We propose two explanations. On the one hand, it would be the evidence that airlines exploit consumer bounded rationality. Actually, a common wisdom among travellers is "the later you buy, the more you pay the ticket", thus price sensitive consumers tend to buy in advance. Airlines, aware of this, can extract a greater surplus by posting moderately higher fares for very-early purchasers that will buy tickets believing to pay the cheapest fares. On the other hand, a higher fare for very-early purchasers can be considered as a fee for risk-aversion.

Coefficients of control variable are those one might expect. The coefficient of *Holiday* is positive and significant. During peak-periods airlines exploit the greater travel demand

[16] Gaggero (2010) suggests that it reflects a pattern opposite to that of travellers' demand elasticity. Bilotkach et (2012) provide evidence that a fare drop is an indication that the actual demand is not as expected, therefore it responds to the need of raising the load factor.

and set 21 to 24% higher fares than off-peak periods. The coefficient of *LCC* is negative and significant.[17] In regressions with *Market Share*, LCCs appear to price 23% lower than FSCs, whilst in regressions with *HHI* as predictor, LCCs appear to price 41% lower than FSCs. The different impact is due to coexistence of *Market Share* and *LCC* in the same regressions. Actually, *Market Share* takes lower values when a carrier is a low cost, thus it already capture the effect on fares induced by *LCC*.

Table 7 shows the results of the Extended Model I. *Booking Day* is still negative and significant, while its interaction with *Market Share* or *HHI* is positive and significant. The negative impact of *Booking Day* reduces in less competitive markets, therefore competition does not prevent airlines from using IPD strategies.

[17] In line with Bergantino (2009). She highlights that LCCs post half the fares of FSCs on some Italian connection on small airports.

TABLE 7

Extended Model I

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0049***	0.0051***	0.0043***	0.0047***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
Booking Day	-0.0166***	-0.0375***	-0.0171***	-0.0374***
	(0.0008)	(0.0015)	(0.0013)	(0.0016)
Booking Day^2		0.0004***		0.0004***
		(0.0000)		(0.0000)
*Market Structure*Booking Day*	0.0001***	0.0001***	0.0001**	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Holidays	0.2088***	0.2118***	0.2321***	0.2348***
	(0.0521)	(0.0522)	(0.0554)	(0.0554)
LCC	-0.2263***	-0.2271***	-0.4049***	-0.4060***
	(0.0424)	(0.0424)	(0.0324)	(0.0325)
Hausman Test statistic	0.942	2.325	0.109	1.709
Hausman Test p-value	0.624	0.508	0.947	0.635
Observations	19,605	19,605	19,605	19,605

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported. *** p<0.01, ** p<0.05, * p<0.1.

The marginal effect of *Booking Day* is now given by $\frac{\partial \ln(P_{it})}{\partial Booking\ Day} = -0.0375 + 2 * (0.0004)\ Booking\ Day_t - (0.0001) Market\ Share_i$ or $\frac{\partial \ln(P_{it})}{\partial Booking\ Day} = -0.0374 + 2 * (0.0004)\ Booking\ Day_t - (0.00004)\ HHI_i$. In Table 8 we report the partial effects for values of *Booking Day* setting *Market Share* and *HHI* equal to the sample mean. We compare these results with those obtained from the baseline regression (no interaction).

TABLE 8

The marginal effect of Booking Day (BD) on fares

by 1% increase of Market Share/HHI

BD	β (*no interaction*)	β (*Market Share*)	β (*HHI*)
5	-0.0313	-0.0294	-0.0312
10	-0.0273	-0.0254	-0.0272
15	-0.0233	-0.0214	-0.0232
20	-0.0193	-0.0174	-0.0192
25	-0.0153	-0.0134	-0.0152
30	-0.0113	-0.0094	-0.0112
35	-0.0073	-0.0054	-0.0072
40	-0.0033	-0.0014	-0.0032
45	0.0007	0.0026	0.0008
50	0.0047	0.0066	0.0048
55	0.0087	0.0106	0.0088
60	0.0127	0.0146	0.0128

In less competitive city-pair markets, the J-curve appears to be flattened. Differences between fares posted in different booking days are less pronounced. This finding is in favour of competitive-type price discrimination, in line with Borestein and Rose (1994), Stavins (2001) and Giaume and Guillou (2004) and contrasting with Gerardi and Shapiro (2007) and Gaggero and Piga (2011).

Table 9 illustrates the results of the Extended Model II by which we investigate IPD further. We test whether airlines adjust their pricing behaviour during phases of a greater travel demand. To this end, we add to the regression equation the interaction between *Booking Day* and *Holiday*, which has a positive and significant impact on fares.

TABLE 9

Extended Model II

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0064***	0.0064***	0.0057***	0.0057***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Booking Day	-0.0154***	-0.0355***	-0.0154***	-0.0355***
	(0.0009)	(0.0015)	(0.0009)	(0.0015)
Booking Day^2		0.0004***		0.0004***
		(0.0000)		(0.0000)
Holidays	0.0544	0.0763	0.0773	0.0992*
	(0.0572)	(0.0564)	(0.0602)	(0.0594)
*Holidays*Booking Day*	0.0064***	0.0056***	0.0064***	0.0056***
	(0.0009)	(0.0008)	(0.0009)	(0.0008)
LCC	-0.1279***	-0.1462***	-0.3068***	-0.3255***
	(0.0476)	(0.0465)	(0.0378)	(0.0364)
*LCC*Booking Day*	-0.0042***	-0.0034***	-0.0042***	-0.0034***
	(0.0009)	(0.0008)	(0.0009)	(0.0008)
Hausman Test statistic	9.329	10.809	10.505	12.133
Hausman Test p-value	0.025	0.029	0.015	0.016
Observations	19,605	19,605	19,605	19,605

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported. *** p<0.01, ** p<0.05, * p<0.1.

The effect of *Booking Day* on fares for peak periods is 0.56% to 0.64% lower than for off-peak periods. Basically this is due to two facts. One the one hand, the greater travel demand allows airlines to decrease IPD because they can sell all the seats with no need of discounted fares. On the other hand, during holidays travellers are more homogeneous, as people journey mainly for tourism. IPD, being based on the heterogeneity of travellers, becomes less effective.

Furthermore, we focus on IPD strategies implemented by LCCs. To this end we employ the interaction between the *Booking Day* and *LCC*, which has a negative impact on fares. The effect of *Booking Day* on posted fares is 0.34% to 0.42% higher for LCCs than FSCs. LCCs engage in a stronger IPD, in line with the more aggressive pricing behaviour of LCCs.

VI SUMMARY AND CONCLUSIONS

This paper explored pricing in air transportation for short-haul markets removing the influence of intermodal competition. To that end, we use a unique dataset on the southern Italian market that exhibits a limited intermodal competition, thus airline pricing strategies are the straight results of air-related competition.

Basically, we dealt with two issues. The first is to measure the extent to which intramodal competition determines fares. The second is to shed light on the intertemporal profile of fares to verify if airlines engage in IPD and whether IPD is of monopolistic-type or competitive-type.

Results are robust across regressions. Further, the robust Hausman test shows that RE GLS estimator provides consistent estimates.

We found that airlines exploit their dominant position on a city-pair. When the intramodal competition reduces, airlines post higher fares. Indeed, 10% increase in *Market Share* leads to 6.4% higher fares and 10% increase of *HHI* leads to 5.7% higher fares. Further, we provided that airlines do undertake IPD and that fare intertemporal profile appears to be non-monotonic, resembling a J-curve. *Booking Day* has a negative effect of fares until the turning point is reached at the 44^{th} day before departure. Beyond that day, it has a positive impact on fares. We claim that a non-monotonic effect would be, on the one hand, the evidence that airlines exploit consumer bounded rationality. Actually, a common wisdom among travellers is "the later you buy, the more you pay the ticket", thus price sensitive consumers tend to buy in advance. Airlines, aware of this, can extract a greater surplus by posting moderately higher fares for very-early purchasers that will buy tickets believing to pay the cheapest fares. On the other hand, a higher fare for very-early purchasers can be considered as a fee for risk-aversion. The empirical evidence is in favor of competitive-type price discrimination: a more competitive market structure fosters the implementation of IPD. Basically, in less competitive city-pair markets, the J-curve appears to be flattened. Finally, airline pricing strategies differ depending on carrier type. LCCs seem to adopt a more aggressive pricing behaviuor as on average they set lower fares and undertake stronger IPD strategies.

One might say that price discrimination is only beneficial for airlines. However, in more competitive markets airlines charge lower fares that, together with the IPD, allow them to target larger segments of demand, which leads to a "democratisation" of air travel. This is very important for areas as southern Italy where the intermodal competition is limited.

Developments for future research could be an enlargement of the territorial coverage in order to compare different exogenously determined accessibility conditions and, thus, to measure the impact of air-related competition on accessibility. Finally, we aim to take into account the local government subsidies often granted to airlines, to evaluate their impact on fares and pricing strategies and, thus, on the net welfare of the area in question.

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Appendix: Robustness check

We have distinguished between carriers of two types: FSCs and LCCs. Indeed, we have assumed similar operating characteristics and pricing behaviour within types. For robustness check we verify whether the results hold when a more detailed distinction in made and *carrier dummies* are added to the model (see Table 10 to 11).

TABLE 10

Baseline Model with carrier dummies.

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0068***	0.0063***	0.0051***	0.0051***
	(0.0012)	(0.0011)	(0.0009)	(0.0009)
Booking Day	-0.0141***	-0.0353***	-0.0141***	-0.0353***
	(0.0005)	(0.0013)	(0.0005)	(0.0013)
Booking Day^2		0.0004***		0.0004***
		(0.0000)		(0.0000)
Holidays	0.2253***	0.2359***	0.2307***	0.2339***
	(0.0435)	(0.0442)	(0.0448)	(0.0449)
Hausman Test statistic	0.011	1.821	0.065	2.541
Hausman Test p-value	0.916	0.402	0.798	0.281
Observations	19,605	19,605	19,605	19,605

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 11

Extended Model I with carrier dummies.

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0047***	0.0049***	0.0036***	0.0041***
	(0.0012)	(0.0012)	(0.0010)	(0.0010)
Booking Day	-0.0166***	-0.0375***	-0.0171***	-0.0374***
	(0.0008)	(0.0015)	(0.0013)	(0.0016)
Booking Day^2		0.0004***		0.0004***
		(0.0000)		(0.0000)
*Market Structure*Booking Day*	0.0001***	0.0001***	0.0001**	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Holidays	0.2333***	0.2363***	0.2318***	0.2346***
	(0.0441)	(0.0442)	(0.0448)	(0.0448)
Hausman Test Statistic	0.088	2.081	0.119	2.666
Hausman Test p-value	0.957	0.556	0.942	0.446
Observations	19,605	19,605	19,605	19,605

Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported. *** p<0.01, ** p<0.05, * p<0.1.

Estimates do not change when we make more specific hypotheses about the behaviour of each carrier.

As stated in section 3, we have assumed exogeneity of market structure. However, Borenstein (1989) argued that market structure could be a function of the fares charged. In our model *Market Share* and *HHI* are potentially correlated with ε_{it}. We employ the GMM estimator as a further robustness check to test the exogeneity of *Market Share* and *HHI.* We use instruments designed by Borenstein (1989) and largely adopted in the related literature[18].

[18] For a fuller description of the instruments see Borenstein (1989) pg 351-353.

Market Share is instrumented with *GENP* and Log*(Distance)*, whilst *HHI* is instrumented with *QHHI* and Log*(Distance)*.

GENP is the observed carrier's geometric mean of enplanements at the endpoints divided by the sum across all carriers of the geometric mean of each carrier's enplanements at the endpoint airports:

$$GENP = \frac{\sqrt{ENP_{k,1} * ENP_{k,2}}}{\sum \sqrt{ENP_{j,1} * ENP_{j,2}}} \tag{6}$$

where k is the observed airline and j refers to all airlines.

QHHI is the square of the market share fitted value plus the rescaled sum of the squares of all other carriers' shares:

$$QHHI = \widehat{MS} + \frac{HHI - MS^2}{(1 - MS)^2}\left(1 - \widehat{MS}\right)^2 \tag{7}$$

where MS stands for the *Market Share* and $\widehat{MS}$ is the fitted value of MS from the first stage regression.

Log*(Distance)* is the logarithm of the distance in kilometres between the two route endpoints.

In the extended model we add the interaction between *Booking Day* and *Market Share* or *HHI*. The interaction could be endogenous too, thus we include as an additional instrument the interaction between *Booking Day* and *GENP* or *QHHI*, respectively.

Airport data were collected to define the daily number of flights of each company and the data about demand. Data on the distance between the two route endpoints are taken from the World Airport Codes web site (http://www.world-airport-codes.com).

From Table 12 to 14 we show GMM estimates using Borenstein (1989) instruments[19]. In the bottom of each table we report the results of some tests. The first one concerns the non-weakness of instruments. For all the regressions, the Kleibergen-Paap rk statistic - the

[19] Current data on number of passengers do not cover the whole sample of round trip fares, so estimations are carried out on a smaller sample.

robust analog of the Cragg-Donald statistic - is far greater than the critical value[20], therefore the null of weakness of instruments is strongly rejected. The second one is the Hansen J Test on the validity of the population moment conditions. For all the regressions, we fail to reject the null hypothesis that the overidentifying restriction is valid. Finally, the third one is the Exogeneity Test for market structure variables. We fail to reject the null hypothesis of exogeneity of either *Market Share* or *HHI* for all the specifications.

GMM estimates are also very close to the RE GLS estimates, which underlines the robustness of the results.

[20] Critical values were computed by Stock and Yogo (2005) for the Cragg-Donald Statistic which assumes i.i.d errors. Results need to be interpreted with caution only if the Kleibergen-Paap rk Statistic is close to the critical values.

TABLE 12

Baseline Model. GMM estimation

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0068***	0.0069***	0.0079***	0.0080***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Booking Day	-0.0136***	-0.0331***	-0.0135***	-0.0331***
	(0.0005)	(0.0014)	(0.0005)	(0.0014)
Booking Day^2		0.0004***		0.0004***
		(0.0000)		(0.0000)
Holidays	0.1836***	0.1883***	0.1990***	0.2041***
	(0.0597)	(0.0599)	(0.0623)	(0.0624)
LCC	-0.2481***	-0.2460***	-0.4281***	-0.4286***
	(0.0555)	(0.0556)	(0.0374)	(0.0374)
Kleibergen-Paap statistic	114.9	114.9	355.2	355.4
Hansen J Test statistic	0.064	0.054	0.048	0.039
Hansen J Test p-value	0.800	0.817	0.827	0.844
Endogeneity Test statistic	0.058	0.031	2.780	2.741
Endogeneity Test p-value	0.809	0.860	0.096	0.098
Observations	16,476	16,476	16,476	16,476

Stock and Yogo (2005) critical value is 19.93. Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 13

Extended Model I. GMM estimation.

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0055***	0.0057***	0.0067***	0.0068***
	(0.0014)	(0.0013)	(0.0013)	(0.0013)
Booking Day	-0.0159***	-0.0350***	-0.0161***	-0.0354***
	(0.0011)	(0.0016)	(0.0014)	(0.0018)
Booking Day^2		0.0004***		0.0004***
		(0.0000)		(0.0000)
*Market Structure*Booking Day*	0.0001**	0.0000**	0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Holidays	0.1842***	0.1888***	0.1995***	0.2045***
	(0.0597)	(0.0598)	(0.0624)	(0.0624)
LCC	-0.2472***	-0.2452***	-0.4278***	-0.4283***
	(0.0554)	(0.0554)	(0.0373)	(0.0374)
Kleibergen-Paap rk statistic	76.80	76.82	233.8	233.9
Hansen J Test statistic	0.062	0.053	0.043	0.035
Hansen J Test p-value	0.803	0.819	0.835	0.852
Endogeneity Test Statistic	0.658	1.064	3.644	2.810
Endogeneity Test p-value	0.720	0.587	0.162	0.245
Observations	16,476	16,476	16,476	16,476

Stock and Yogo (2005) critical value is 14.43. Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 14

Extended Model II. GMM estimation.

	Market Share		*HHI*	
	(1)	(2)	(3)	(4)
Market Structure	0.0068***	0.0069***	0.0079***	0.0080***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Booking Day	-0.0137***	-0.0323***	-0.0133***	-0.0320***
	(0.0010)	(0.0015)	(0.0010)	(0.0015)
Booking Day^2		0.0003***		0.0003***
		(0.0000)		(0.0000)
Holidays	0.0683	0.0848	0.0880	0.1049
	(0.0639)	(0.0633)	(0.0666)	(0.0659)
*Holidays*Booking Day*	0.0046***	0.0041***	0.0044***	0.0039***
	(0.0009)	(0.0009)	(0.0010)	(0.0009)
LCC	-0.1147**	-0.1276**	-0.2855***	-0.3008***
	(0.0579)	(0.0564)	(0.0407)	(0.0392)
*LCC*Booking Day*	-0.0054***	-0.0048***	-0.0057***	-0.0051***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Kleibergen-Paap rk Statistic	115.2	115.2	356.4	356.6
Hansen J Statistic	0.088	0.074	0.070	0.057
Hansen J p-value	0.767	0.786	0.791	0.812
Endogeneity Test Statistic	0.032	0.016	3.043	2.967
Endogeneity Test p-value	0.857	0.900	0.081	0.085
Observations	16,476	16,476	16,476	16,476

Stock and Yogo (2005) critical value is 19.93. Standard errors (in parentheses) are clustered at flight level. Control dummies are always included but not reported.

*** p<0.01, ** p<0.05, * p<0.1.